

FORECASTING FINANCIAL DISTRESS OF PN17 COMPANIES IN MALAYSIA USING LOGISTIC REGRESSION

(Ramalan Kesulitan Kewangan Syarikat PN17 di Malaysia Menggunakan Regresi Logistik)

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ABSTRACT

This study aims to predict financial distress among Malaysian companies included in Practice Note 17 (PN17). The analysis examines a sample of 35 companies classified as PN17 from 2014 to 2023. To create a balanced comparison, these companies are matched with 35 non-PN17 companies, resulting in a total sample size of 70 firms. Logistic regression was employed in this study because the financial ratios do not need to be normally distributed. The findings indicate that the model is most effective in the near term, specifically during the year of financial difficulty and up to one year prior to the occurrence, when it achieves the highest level of prediction accuracy. Financial metrics, including working capital, retained earnings, and earnings before interest and taxes (EBIT) are crucial in assessing a company's probability of experiencing financial difficulties, underscoring the vital need of liquidity, profitability, and financial soundness. However, when the prediction timeframe extends beyond two years, the model's precision decreases, highlighting the limitations of using conventional financial ratios for long-term forecasts. This suggests that while logistic regression is a valuable method for predicting short-term distress, its effectiveness diminishes in early-stage forecasts, when distress indicators are less prominent.

Keywords: financial distress; logistic regression; Malaysia

ABSTRAK

Kajian ini bertujuan untuk meramal kesulitan kewangan dalam kalangan syarikat Malaysia yang termasuk dalam Notis Amalan 17 (PN17). Analisis ini mengkaji sampel sebanyak 35 syarikat yang diklasifikasikan sebagai PN17 dari tahun 2014 hingga 2023. Untuk membuat perbandingan yang seimbang, syarikat-syarikat ini dipadankan dengan 35 syarikat bukan PN17, menghasilkan jumlah saiz sampel sebanyak 70 firma. Regresi logistik digunakan dalam kajian ini kerana nisbah kewangan tidak perlu mengikuti taburan normal. Penemuan menunjukkan bahawa model ini paling berkesan dalam jangka masa pendek, khususnya semasa tahun kesulitan kewangan dan sehingga satu tahun sebelum kejadian, apabila ia mencapai tahap ketepatan ramalan tertinggi. Metrik kewangan, termasuk modal kerja, pendapatan tersimpan, dan pendapatan sebelum faedah dan cukai (EBIT) adalah penting dalam menilai kemungkinan sesebuah syarikat mengalami kesulitan kewangan, menekankan kepentingan kecairan, keuntungan, dan kestabilan kewangan. Walau bagaimanapun, apabila tempoh ramalan melebihi dua tahun, ketepatan model berkurangan, menunjukkan had penggunaan nisbah kewangan konvensional untuk ramalan jangka panjang. Ini bermakna bahawa walaupun regresi logistik adalah kaedah yang berguna untuk meramalkan kesulitan jangka pendek, keberkesanannya berkurangan dalam ramalan peringkat awal apabila petunjuk kesulitan kurang ketara.

Kata kunci: kesulitan kewangan; regresi logistik; Malaysia

1. Introduction

Today, the ability to forecast financial difficulties has grown in importance. Businesses, investors, and governments can all benefit from timely and accurate distress forecasts, which enable them to take proactive steps to reduce risks and avoid negative consequences. While logistic regression is a widely used approach in financial distress prediction, this study uniquely applies it within the Malaysian regulatory context of PN17 companies from 2014 to 2023, utilizing a distinct dataset that combines specific financial ratios tailored to reflect the operational realities of Malaysian firms, thereby contributing original insights into the effectiveness of this method in predicting financial distress in this particular regulatory framework. Despite the abundance of research conducted on distress prediction in recent decades, there is a significant need for ongoing efforts to enhance the precision of prediction models (Bauweraerts 2016). Scholarly research on the modeling of company financial difficulty begins with the groundbreaking studies conducted by Beaver (1966) and Altman (1968) which rely on financial ratios.

Financial distress refers to a condition in which a corporation encounters financial challenges, ultimately impairing its ability to meet financial commitments and potentially leading to insolvency or liquidation (Shakya & Parab 2024). As noted by Say (2024), financial difficulties arise when a company's cash flows are insufficient to cover obligations, thus increasing business risk and potentially resulting in asset depletion or bankruptcy.

In Malaysia, Bursa Malaysia serves as the stock market regulator, implementing frameworks like Practice Note No. 4/2001 (PN4) and Practice Note No. 17/2005 (PN17) to address financial distress among companies (Alifiah 2014). The PN17 framework is essential for ensuring the financial health and sustainability of public-listed companies, specifying criteria for classifying organizations as financially distressed (Bursa Malaysia 2015).

This research seeks to forecast the likelihood of financial distress leading to PN17 classification among Malaysian companies by adopting logistic regression. Unlike traditional models such as Altman's Z-score, which may not fully capture the complexities of the Malaysian market, this study emphasizes the potential of logistic regression to enhance predictive accuracy by considering both financial and non-financial indicators. Specifically, it explores how integrating non-financial data, such as textual sentiments from company reports and market information, can improve prediction models that primarily focus on classical financial measures.

Additionally, this study investigates the predictive nature of financial ratios from T to $T-5$, aiming to provide insights into effectively deploying logistic regression models at relevant stages based on how predictive power changes as the distress event approaches. By addressing these aspects, this research contributes to the existing literature by highlighting the strengths and limitations of logistic regression in predicting financial distress, ultimately offering practical insights for stakeholders involved in financial decision-making.

2. Literature Review

The prediction of financial distress has emerged as a crucial area of research in finance, driven by the need for early warning systems that can help stakeholders make informed decisions. Understanding the complexities of financial distress is essential for businesses, investors, and regulators, particularly in the Malaysian context, where unique economic factors play a significant role.

Historically, models such as Altman's Z-score (Altman 1968) and Ohlson's logit model Ohlson (1980) have laid the groundwork for assessing corporate financial health. The Z-score model, known for its high predictive accuracy, leverages financial ratios to estimate the likelihood of bankruptcy. However, its reliance on historical data may limit its applicability in rapidly changing economic environments (Rosle *et al.* 2024). Ohlson's logit model similarly emphasizes financial ratios but has been critiqued for not capturing the full spectrum of factors influencing financial distress.

In recent years, logistic regression analysis (LRA) has become more popular as a flexible method for predicting financial distress. LRA's simplicity and interpretability make it appealing, and studies have shown it to be effective in various contexts (Altman *et al.* 2017). Nevertheless, traditional logistic regression faces challenges, particularly in handling complex, non-linear data patterns, which has led researchers to explore machine learning techniques as viable alternatives.

In the Malaysian context, numerous studies have applied Multiple Discriminant Analysis (MDA) to predict financial distress (Fauzias & Chin 2001; Chin 2005; Hiong *et. al* 2021). However, MDA's assumptions often do not hold true in practice, leading to limitations in its effectiveness (Karels & Prakash 1987). This has prompted a shift toward logistic regression and machine learning techniques, as researchers aim to improve prediction models' reliability.

Hence, in response to the constraints of MDA, several studies have been conducted by employing logistic regression analysis (LRA). LRA has been extensively employed as a statistical method for financial distress prediction since the foundational work of Ohlson (1980). The simplicity and clarity of logistic regression make it very appealing for analyzing the probability of corporate failure. Multiple studies have validated its effectiveness by combining financial ratios with logistic models, showing robust results in various contexts (Altman *et. al* 2017).

In their study, Bukhori *et al.* (2022) applied logistic regression to examine how liquidity, activity, leverage, and sales growth signal financial distress before bankruptcy stage of manufacturing companies listed on the Indonesia Stock Exchange. Asutay and Othman (2020) measured financial distress among Malaysian Islamic Banks using a multivariate logit model.

Singh and Singla (2019), through the utilization of logistic regression, forecasted bankruptcy by applying the Altman Z-Score model. They discovered that the overall correct classification rate climbed to 81.10% when the model was re-estimated using the most recent data. Furthermore, the rate increased to 87.83% when logistic regression was applied to the process of re-estimating the model.

Throughout the years, research has expanded logistic regression models by incorporating additional variables such as macroeconomic factors and governance indicators to enhance prediction accuracy. For instance, Munoz *et al.* (2020) combined accounting and auditing variables in a logistic regression framework, illustrating its continued relevance in modern financial distress prediction models. Nevertheless, the literature also emphasizes that there are limitations with traditional logistic regression, especially in handling complex data patterns compared to newer machine learning techniques.

Yazdanfar and Öhman (2020) investigated financial hardship causes during and after the global financial crisis among 3865 Swedish small and medium enterprises (SMEs) in five industries from 2008 to 2015 using logistic regression. They found that financial distress is affected by macroeconomic variables and firm-specific features, even though business size and industry affiliation have no significant impact on financial distress.

Machine learning models, such as decision trees and random forests, have been shown to improve predictive accuracy by uncovering intricate relationships within data that traditional models may overlook. For instance, Ishak *et al.* (2024) demonstrated that machine learning

techniques outperform logistic regression in specific contexts, highlighting the need for a comparative analysis of these methodologies in the realm of financial distress prediction.

Cao *et al.* (2022) implemented a Bayesian network model and machine learning to predict bankruptcy among 32,344 United States firms from 1961 to 2018. Zhao *et al.* (2023) forecasted financial distress by applying machine learning methods such as support vector machine, random forest, XGBoost, and logistic regression.

Despite the wealth of literature, a notable gap exists regarding the application of logistic regression to predict financial distress among PN17 companies specifically. This research seeks to address this gap by examining the effectiveness of logistic regression and exploring the integration of non-financial indicators alongside traditional financial measures. By critically analysing existing studies and their methodologies, this paper aims to contribute valuable insights into the evolving landscape of financial distress prediction.

In summary, while significant progress has been made in the field of financial distress prediction, ongoing efforts are necessary to enhance model accuracy and applicability. This study will build upon existing literature and provide practical recommendations for stakeholders in the Malaysian corporate sector.

3. Methodology

3.1 Data

This study utilizes a quantitative research approach to construct a logistic regression model for predicting financial distress among Malaysian companies. The focus is specifically on companies listed under PN17 from 2014 to 2023. The PN17 categorization identifies companies in financial distress according to Bursa Malaysia regulations. The study analyzes a sample of 35 companies that were classified as PN17 during this period. To create a balanced comparison, these companies are matched with 35 non-PN17 companies, resulting in a total sample size of 70 firms. The matching criteria include sector and company size, measured by the nearest total asset value during the same financial period, to mitigate selection bias when forming the control group. Financial data was collected from a database called Eikon Datastream (Excel Add-In function) and encompassed essential financial indicators such as sales, EBIT, total assets, current assets, current liabilities, total liabilities, retained earnings, and market value of equity. The data was collected over multiple time points to capture the financial evolution leading up to the PN17 classification.

T: The year when the company was declared as PN17

T - 1: 1 year before being declared as PN17

T - 2: 2 years before being declared as PN17

T - 3: 3 years before being declared as PN17

T - 4: 4 years before being declared as PN17

T - 5: 5 years before being declared as PN17

This multi-period analysis enables a longitudinal evaluation of financial patterns leading to distress. The selected data samples are summarized in Table 1.

3.2 Model development

To develop the prediction model, a logistic regression analysis was conducted. Logistic regression is suitable for binary classification problems, where the dependent variable is categorical. In this study, we define the dependent variable *Y* as a categorical variable where:

- *Y* = 1 indicates that a company is classified as PN17 (financially distressed),

- $Y = 0$ indicates that a company is classified as non-PN17 (not financially distressed).

Table 1: Selected Data Sample for Analysis

PN17 Samples	Frequency	Percentage (%)	Non-PN17 Samples	Frequency	Percentage (%)
Consumer Products and Services	9	25.71	Consumer Products and Services	9	25.71
Construction	2	5.71	Construction	2	5.71
Energy	6	17.14	Energy	6	17.14
Healthcare	1	2.86	Healthcare	1	2.86
Industrial Products and Services	9	25.71	Industrial Products and Services	9	25.71
Property	3	8.57	Property	3	8.57
Telecommunications and Media	2	5.71	Telecommunications and Media	2	5.71
Transportation and Logistic	3	8.57	Transportation and Logistic	3	8.57
Total	35	100.00	Total	35	100.00

The financial ratios used in this research are based on Altman's Z-Score model that was developed in 1968 (Altman 1968). Let P_1 is Working Capital, P_2 is Retained Earnings, P_3 is EBIT, P_4 is Total Liabilities, P_5 is Market Value of Equity, P_6 is Sales and P_7 is Total Assets. The financial ratios can be expressed as follows:

$$X_1 = \frac{P_1}{P_7}, X_2 = \frac{P_2}{P_7}, X_3 = \frac{P_3}{P_7}, X_4 = \frac{P_4}{P_5} \text{ and } X_6 = \frac{P_6}{P_7} \quad (1)$$

The liquidity ratio, X_1 is defined as the ratio of a company's capital to its total assets. Working capital is calculated by the difference between current assets and current liabilities (Lessambo 2018). This ratio evaluates the company's capacity to cover its short-term obligations with its current assets (Rahman & Acharya 2022). A higher liquidity ratio indicates a lower risk of financial distress, as it suggests that the company has more readily available resources to meet its short-term liabilities.

The profitability ratio, X_2 measures the relationship between retained earnings and total assets. This ratio assesses the company's historical performance by quantifying the accumulated profits that have contributed to its total assets (Azam *et al.* 2023). A company with a higher profitability ratio demonstrates consistent earnings, reflecting its ability to maintain profits over time without relying on external debt or equity financing.

The productivity ratio, X_3 defined as EBIT divided by total assets, examines a company's operational efficiency. A higher productivity ratio indicates that the company is effectively utilizing its assets to generate operating profits, which suggests a lower likelihood of financial distress (Ibrahim *et al.* 2024).

The leverage ratio, X_4 measures a company's equity availability to cover liabilities (Ibrahim *et al.* 2024). A company is considered to be in a more stable financial position when it has a higher leverage ratio, indicating stronger equity protection relative to its liabilities.

Finally, the capital turnover ratio, X_5 also known as the asset turnover ratio, is calculated by dividing sales by total assets. This ratio indicates how efficiently a company utilizes its

assets to generate revenue. A higher capital turnover ratio signifies that the company is proficient in converting its assets into sales.

To model the relationship between the dependent variable, Y and the independent variables X_1, X_2, X_3, X_4 and X_5 , we utilize logistic regression, which estimates the probability that $Y=1$. We denote this probability as p . The relationship between the probability, p and the independent variables is modeled using the logit function, which transforms the probability into log-odds:

$$\text{logit}(p) = \ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_5 X_5 \quad (2)$$

where

p = the probability of a company being classified as PN17,

β_0 = the intercept,

$\beta_1, \beta_2, \dots, \beta_5$ = coefficients of the independent variables (financial ratios),

$X_1, X_2, \dots, X_5$ = independent variables representing the financial ratios.

A comprehensive analysis of the financial ratios utilized in the model is essential for understanding their relevance in predicting financial distress. Each ratio is critically assessed based on its historical performance and correlation with financial difficulties. For instance, during Covid-19 pandemic, Malaysian companies faced challenges in financial ratios that affected by the management practices and economic conditions. Historical trends and comparisons will be provided to showcase the impact of these ratios over the years leading up to distress.

3.3 Model evaluation and performance

In order to evaluate the LRA model the goodness-of-fit test such as McFadden R^2 , Likelihood ratio (LLR) p -value, and Hosmer-Lemeshow test were applied in this study. McFadden R^2 evaluates the model's goodness-of-fit, whereby higher values indicate better model performance. Meanwhile, Likelihood Ratio (LLR) p -value tests the entire significance of the model. A low p -value indicates that the model is statistically significant. Lastly, the Hosmer-Lemeshow Goodness-of-Fit Test evaluates how well the predicted values match the actual outcomes. A higher p -value (>0.05) suggests a good fit.

The Variance Inflation Factor (VIF) was also used to identify multicollinearity in the model via computing the inflated variance of a regression coefficient, R^2 . VIF is usually computed during regression or correlation analysis which produces the R^2 values that can then be substituted into the VIF formula (Vorosmarty & Dobos 2020). The VIF is calculated as:

$$VIF = \frac{1}{1 - R^2} \quad (3)$$

Next, the model's accuracy was assessed using standard classification metrics, receiver operating characteristic (ROC) curve, and area under the curve (AUC). These measures help determine how effectively the model differentiates between PN17 and non-PN17 companies.

4. Results

This section presents the findings from the logistic regression analysis conducted to predict financial distress among PN17 companies, including necessary diagnostic checks.

4.1 Descriptive statistics

Descriptive statistics were calculated for each financial ratio across different time periods. The mean and standard deviation (SD) for each variable is summarized separately in Table 2 below.

Table 2: Descriptive statistics

Model	X_1		X_2		X_3		X_4		X_5	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Model 1 (Overall)	0.0849	0.4495	-0.0746	0.5734	-0.0146	0.3426	1.8725	3.4740	0.6153	0.4717
Model 2 T	-0.0966	0.8682	-0.3563	1.1053	-0.1369	0.4010	1.7846	4.6529	0.5624	0.5055
Model 3 $T - 1$	0.0442	0.3702	-0.1300	0.4709	-0.0523	0.1786	1.4228	1.9776	0.6092	0.5123
Model 4 $T - 2$	0.1193	0.3015	-0.0533	0.3727	-0.2808	0.1180	1.6318	2.4169	0.6063	0.5136
Model 5 $T - 3$	0.1541	0.2676	0.0139	0.3002	0.0010	0.0980	2.3368	4.1087	0.6132	0.4363
Model 6 $T - 4$	0.1483	0.2572	0.0577	0.3119	0.1060	0.6661	2.2408	4.034	0.6405	0.4113
Model 7 $T - 5$	0.1403	0.2426	0.0198	0.3291	0.0223	0.1399	1.8181	2.8453	0.6570	0.4519

The positive mean of X_1 in Model 1 suggests that companies generally maintain adequate working capital; however, significant variability indicates disparities in financial stability across firms. By the time companies are classified as PN17, X_1 has shifted into negative territory, signifying critical liquidity challenges. This decline from $T-5$ (0.1403) to T (-0.0966) highlights a clear deterioration in liquidity as companies approach distress. Additionally, the negative mean of X_2 suggests accumulated losses for majority firms, with significant variability reflecting divergent retained earnings performance whereas this trend deteriorates at T (-0.3563), demonstrating increasing difficulties in profit generation and equity retention.

Next, X_3 exhibiting a slightly negative mean, that shows inadequate profitability. X_3 values continues to decline as distress approaches, signalling deteriorating operational efficiency. Generally, X_4 shows equity surpassing liabilities, the high standard deviation indicates substantial variability, particularly at T , where some firms encounter difficulties to manage their financial structure effectively. The overall stability of this ratio masks significant differences in how companies handle liabilities as distress approaches. Finally, X_5 maintains positive but exhibits a gradual decline, pointing to reduced operational efficiency and revenue generation, with moderate variability across companies, emphasising the diverse financial trajectories as distress nears.

4.2 Logistic regression analysis

The logistic regression model coefficients provide insight into the relationship between each financial ratio and the probability of a company being classified as PN17. Table 3 shows the estimates, standard errors, Wald statistics, p -values, and odds ratios for each variable across different time periods.

Any variables with p -values below 0.05 are considered statistically significant. In the overall model, X_1 ($p = 0.000$), X_2 ($p = 0.019$), and X_3 ($p = 0.007$) are significant predictors of financial distress. In the current year (T), X_2 ($p = 0.041$) and X_4 ($p = 0.049$) are significant, indicating that retained earnings and book value of equity are key indicators. In the earlier years ($T-1$ to $T-5$), X_1 remains consistently significant, highlighting its importance in predicting distress. These findings are consistent with that of Ishak et al. (2024).

Table 3: Model estimation

Model	Variables	Estimate Coefficients	Standard Error	Wald Statistics	p -value	Odds Ratio
1 (Overall)	Constant	0.5240	0.202	6.760	0.009	1.689
	X_1	-2.7369	0.515	28.29	0.000	0.0648
	X_2	-0.9137	0.389	5.508	0.019	0.4010
	X_3	-3.6065	1.327	7.388	0.007	0.0271
	X_4	-0.0591	0.044	1.828	0.176	0.9426
	X_5	-0.2797	0.249	1.261	0.261	0.7560
Model 2 (T)	Constant	0.9782	0.648	2.2788	0.131	2.6597
	X_1	-0.4318	1.542	0.0784	0.779	0.6493
	X_2	-2.8521	1.398	4.1621	0.041	0.0577
	X_3	-4.6668	3.361	1.9280	0.165	0.0094
	X_4	-1.4182	0.721	3.8690	0.049	0.2422
	X_5	-1.0907	0.854	1.6311	0.202	0.3360
Model 3 ($T - 1$)	Constant	0.3543	0.517	0.4696	0.493	1.4251
	X_1	-4.0081	1.535	6.8180	0.009	0.0182
	X_2	-0.8228	1.025	0.6444	0.422	0.4392
	X_3	-12.482	4.937	6.3918	0.011	0.0000
	X_4	-0.2877	0.248	1.3459	0.246	0.7500
	X_5	-0.0392	0.674	0.0034	0.954	0.9616
Model 4 ($T - 2$)	Constant	0.5018	0.522	0.9241	0.337	1.6517
	X_1	-3.1607	1.470	4.6230	0.032	0.0424
	X_2	-0.6764	1.116	0.3673	0.544	0.5084
	X_3	-13.0273	4.787	7.4060	0.006	0.0000
	X_4	-0.3188	0.199	2.5664	0.109	0.7270
	X_5	0.1558	0.607	0.0659	0.797	1.1686
Model 5 ($T - 3$)	Constant	0.5238	0.499	1.1018	0.294	1.6884
	X_1	-2.8912	1.267	5.2072	0.023	0.0555
	X_2	-0.8832	0.952	0.8606	0.353	0.4134
	X_3	-3.2374	3.276	0.9766	0.323	25.4674
	X_4	0.0159	0.074	0.0462	0.830	1.0160
	X_5	-0.1667	0.601	0.07693	0.781	0.8464
Model 6 ($T - 4$)	Constant	0.8656	0.550	2.4770	0.115	2.3764
	X_1	-1.0467	1.289	0.6594	0.417	0.3511
	X_2	-1.2956	1.049	1.5254	0.217	0.2737
	X_3	-5.2959	3.999	1.7538	0.185	0.0050
	X_4	-0.0835	0.113	0.5460	0.460	0.9199
	X_5	-0.4913	0.651	0.5695	0.450	0.6118
Model 7 ($T - 5$)	Constant	0.7950	0.556	2.0444	0.153	2.2144
	X_1	-2.9249	1.278	5.2379	0.022	0.0537
	X_2	-1.4784	1.110	1.7739	0.183	0.2280
	X_3	2.2908	2.818	0.6608	0.416	9.8828
	X_4	-0.0286	0.102	0.0786	0.779	0.9718
	X_5	-0.5408	0.636	0.7230	0.395	0.5822

The odds ratio in Table 3 represents the likelihood of the PN17 companies undergoing financial distress according to changes in each independent variable. If the odds ratio is less than 1, it indicates that an increase in the variable decreases the probability of facing financial distress. For example, in Model 1, variables X_1 , X_2 and X_3 had odds ratios significantly below

1 which indicates that the higher values in these financial ratios correlate with lower chances of distress.

The models closer to the year of distress (T , $T-1$, $T-2$) generally show better fit and more significant predictors. This is expected as financial ratios become more indicative of distress as companies approach the PN17 event. For earlier periods ($T-3$ to $T-5$), the model's predictive power diminishes, with fewer significant variables and lower odds ratios, indicating that early predictions are more challenging.

The analysis suggests that X_1 , X_2 , and X_3 are critical in predicting financial distress. The predictive power of these variables is strongest closer to the time of distress, while earlier predictions require more cautious interpretation due to fewer significant indicators. This trend is caused by internal company movements or external market conditions. The COVID-19 pandemic in the years (2020–2021) caused some Malaysian companies to experience financial difficulties because of operational interruptions and diminished revenues. For instance, in 2023, the Malaysian capital market remained resilient to ensure adequate liquidity buffers (Securities Commission Malaysia 2024).

4.3 Model evaluation

This section describes the results of goodness-of-fit and diagnostic tests that were conducted to evaluate the LRA model. This section also explains the model's performance using various metrics such as accuracy, precision, recall, F1 score, ROC, and AUC.

4.3.1 Goodness-of-fit test

Table 4 below shows the findings of goodness-of-fit test that have been conducted to evaluate the performance of LRA model in this study.

Table 4: Model fitness

Model	Mc Fadden R^2	LLR p -value	Hosmer Lemeshow (p -value)
1	0.2213	4.195e-26	-0.7805 (1.000)
2	0.5387	4.731e-10	6.5509 (0.586)
3	0.4381	4.637e-08	0.6040 (1.000)
4	0.3893	4.178e-07	5.4834 (0.705)
5	0.1399	0.01854	-12.4618 (1.000)
6	0.1320	0.02526	-1.3941 (1.000)
7	0.1182	0.04274	-2.5038 (1.000)

The McFadden R^2 values indicate how well each model fits the data. Generally, values between 0.2 and 0.4 suggest a decent model fit in logistic regression. The model at time T (the year the company is declared PN17) shows the highest McFadden R^2 , indicating the best fit. The models for one and two years before distress also show relatively strong fits. The McFadden R^2 values decline significantly for the earlier years, suggesting that the model's predictive power weakens as we move further from the year of distress.

The LLR p -values test the overall significance of the models. All models show highly significant p -values which are close to zero, indicating that they are statistically significant. The lowest p -values are observed in Model 2, Model 3, and Model 4, reinforcing that these models are most effective close to the time of the distress event.

The p -values for the Hosmer-Lemeshow test indicate how well the models' predictions align with the actual outcomes. A p -value greater than 0.05 suggests a good fit. These models show adequate fit, indicating that they predict financial distress reasonably well in Model 2

and Model 4. Although some p -values are perfect (1.000), the negative test statistics suggest issues with model calibration, especially in the earlier years (Model 5, Model 6 and Model 7).

The results indicate that the logistic regression models perform best in predicting financial distress within the last two years before the PN17 declaration. As we move further from the distress event, the models become less reliable, as reflected in the lower McFadden R^2 values and potential calibration issues shown in the Hosmer-Lemeshow test.

4.3.2 Diagnostic checking

Diagnostic checks were performed, including multicollinearity assessments. This step is important to validate the assumptions of regression analysis. The multicollinearity test encompasses the dataset of 70 companies. A total of 35 companies from the dataset are classified as PN17 while the remaining 35 companies are non-PN7. It is necessary to check for the presence of multicollinearity in the sample data before using financial ratios in logistic regression analyses. For this purpose, correlation analysis and collinearity diagnostics were performed in this study. Table 5 shows the variance inflation factor (VIF) value for each financial ratio used in the analysis.

Table 5: Multicollinearity Analysis

Variables	Collinearity Statistics
X_1	2.008715
X_2	2.010080
X_3	1.534460
X_4	1.295712
X_5	1.027571

Table 5 above shows the collinearity statistics for all the financial ratios. According to Hair (2010) and Waqas and Md-Rus (2018), a VIF value greater than 10 and tolerance level below 0.1 depict the existence of multicollinearity. Table 5 shows that all the values of VIF are smaller than 10, which also supports the results of correlation and confirms that there is no multicollinearity problem in the data. Hence, all these financial ratios are used as independent variables in the regression analysis for financial distress prediction in this study.

4.4 Model performance

The performance of the logistic regression models in predicting financial distress was evaluated using common classification metrics, ROC curves, and AUC values. Table 6 below illustrates the performance of the classification model across various time intervals, reflecting differing degrees of accuracy, precision, recall, and F1 scores for predicting financial distress (class 1) and non-distress (class 0).

The logistic regression model's performance was evaluated using various metrics, and the overall accuracy was found to be 76%. Key financial ratios, including X_1 – liquidity ratio, X_2 – profitability ratio, and X_3 – productivity, emerged as significant predictors of financial distress among PN17 companies.

The results indicate that certain financial ratios, such as liquidity ratio and profitability ratio, were significant predictors of financial distress. A deeper analysis reveals that these ratios have shown consistent trends in the years leading up to distress events. For example, companies that faced financial difficulties exhibited a notable decline in liquidity ratios two years prior to distress, indicating liquidity challenges. Historical comparisons demonstrate that these financial indicators can serve as early warning signs for stakeholders, highlighting the importance of continuous monitoring.

Table 6: Model performance

Model	Class	Precision	Recall	F1-Score
1 (Overall)	No Distress (0)	0.76	0.72	0.74
	Distress (1)	0.77	0.80	0.78
	Accuracy			0.76
2 (T)	No Distress (0)	0.80	1.00	0.89
	Distress (1)	1.00	0.90	0.95
	Accuracy			0.93
3 ($T - 1$)	No Distress (0)	0.50	0.75	0.60
	Distress (1)	0.88	0.70	0.78
	Accuracy			0.71
4 ($T - 2$)	No Distress (0)	0.43	0.75	0.55
	Distress (1)	0.86	0.66	0.71
	Accuracy			0.64
5 $T - 3$	No Distress (0)	0.38	0.75	0.50
	Distress (1)	0.83	0.50	0.62
	Accuracy			0.57
6 ($T - 4$)	No Distress (0)	0.25	0.75	0.38
	Distress (1)	0.50	0.10	0.17
	Accuracy			0.29
7 ($T - 5$)	No Distress (0)	0.33	0.75	0.46
	Distress (1)	0.80	0.40	0.53
	Accuracy			0.50

As shown in Table 6, the model's predictive accuracy decreases as the forecast horizon extends beyond the year of distress. The ratios' predictive power is particularly strong within the last two years leading to the distress event, reinforcing the need for timely interventions based on these financial indicators.

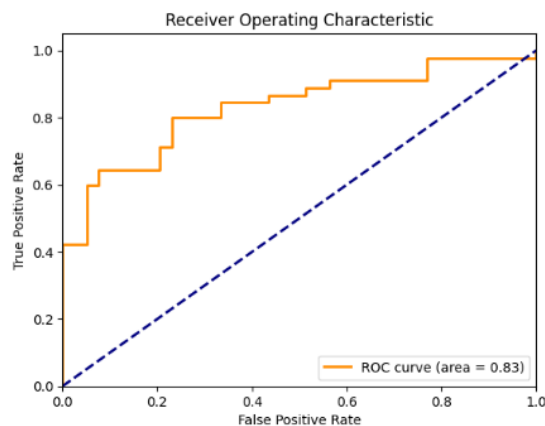


Figure 1: ROC curves for Model 1

In the present year, Model 2 exhibits an accuracy of 0.93, with non-distressed enterprises demonstrating the highest precision and recall at 0.80. Nonetheless, the model's efficacy diminishes as the year of distress nears. The model's accuracy drops to 0.71, with non-distressed enterprises exhibiting the best precision and recall of 0.50. Distressed companies show the highest precision but possess the lowest recall of 0.70. The model's performance declines further from the distress year, with non-distressed enterprises exhibiting the lowest precision and recall at 0.83. The model exhibits inadequate performance in the four years preceding distress, characterized by low precision and recall for distressed firms.

The examination of the ROC curves and AUC values yields significant insights into the performance of the financial distress prediction model across various time intervals. The overall AUC value of 0.83 indicates that the model performs effectively in distinguishing between distressed and non-distressed companies, with strong predictive power. However, a detailed analysis of each time period reveals varying levels of effectiveness, highlighting the model's strengths and limitations as the prediction horizon extends.

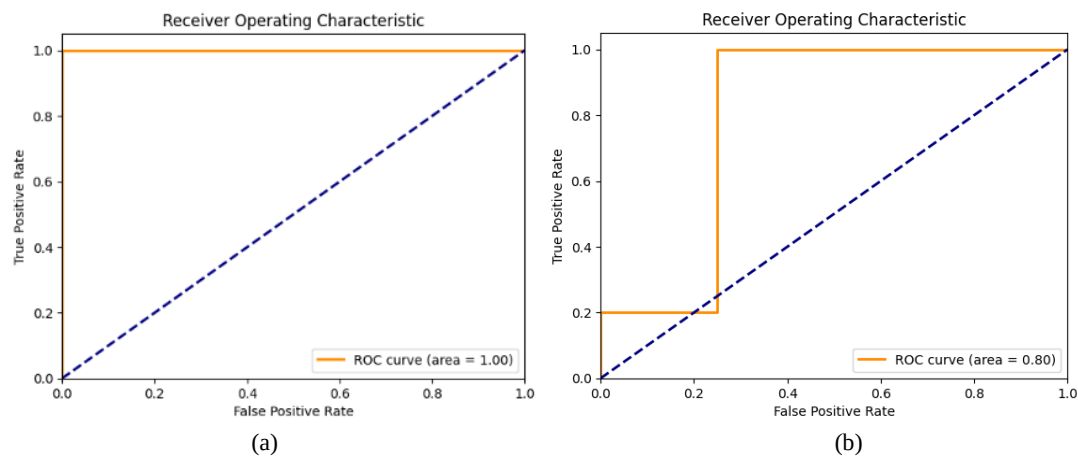


Figure 2: ROC curves for (a) Model 2 and (b) Model 3

In the present year (Model 2), the model attains perfect classification with an AUC of 1.0, indicating that the financial distress signals are most prominent at the point of PN17 declaration. This is expected as companies on the brink of distress display clear signs of financial instability, making predictions highly accurate. One year prior to distress (Model 3), the AUC drops to 0.8, indicating a slight decline in predictive accuracy, but still offering a reliable prediction with an 80% chance of correctly identifying distressed companies.

As the time frame extends to two and three years before distress (Model 4 and Model 5), the model's performance declines, with AUC values of 0.75 and 0.625, respectively. At this stage, early financial distress indicators are less apparent, reducing the model's predictive accuracy. Interestingly, the AUC increases slightly to 0.7 four years before distress (Model 6), which may indicate the emergence of certain latent financial patterns well in advance. However, by five years before distress (Model 7), the AUC drops further to 0.6, signaling that long-term predictions are challenging, with limited reliability.

Overall, the analysis illustrates that the model is most proficient in predicting financial distress within the year of distress and up to one year before the event. As the prediction horizon lengthens, the accuracy diminishes, highlighting the difficulty of making early predictions. These findings emphasize the necessity of close monitoring as companies approach financial distress, where predictive models can offer more reliable insights for timely intervention and decision-making.

5. Discussion

The results of this study provide significant insights into the predictive power of logistic regression models in projecting financial distress among Malaysian companies by examining financial ratios across different time frames leading up to the PN17 classification. Furthermore, the study also has highlighted the strengths and limitations of using logistic regression for this purpose. Several financial ratios have revealed as critical indicators of

financial distress, particularly in the years closer to the distress occurrence. In this study, Model 1 shows that X_1 , X_2 , and X_3 are consistently robust indicators, with significant p -values and low odds ratios where these variables highlight the essential role of liquidity, accumulated earnings, and operating performance in assessing a company's financial stability. As the timeframe extend beyond the distress year, the predictive relevance of these indicators diminishes, reflecting the evolving nature of financial distress signals.

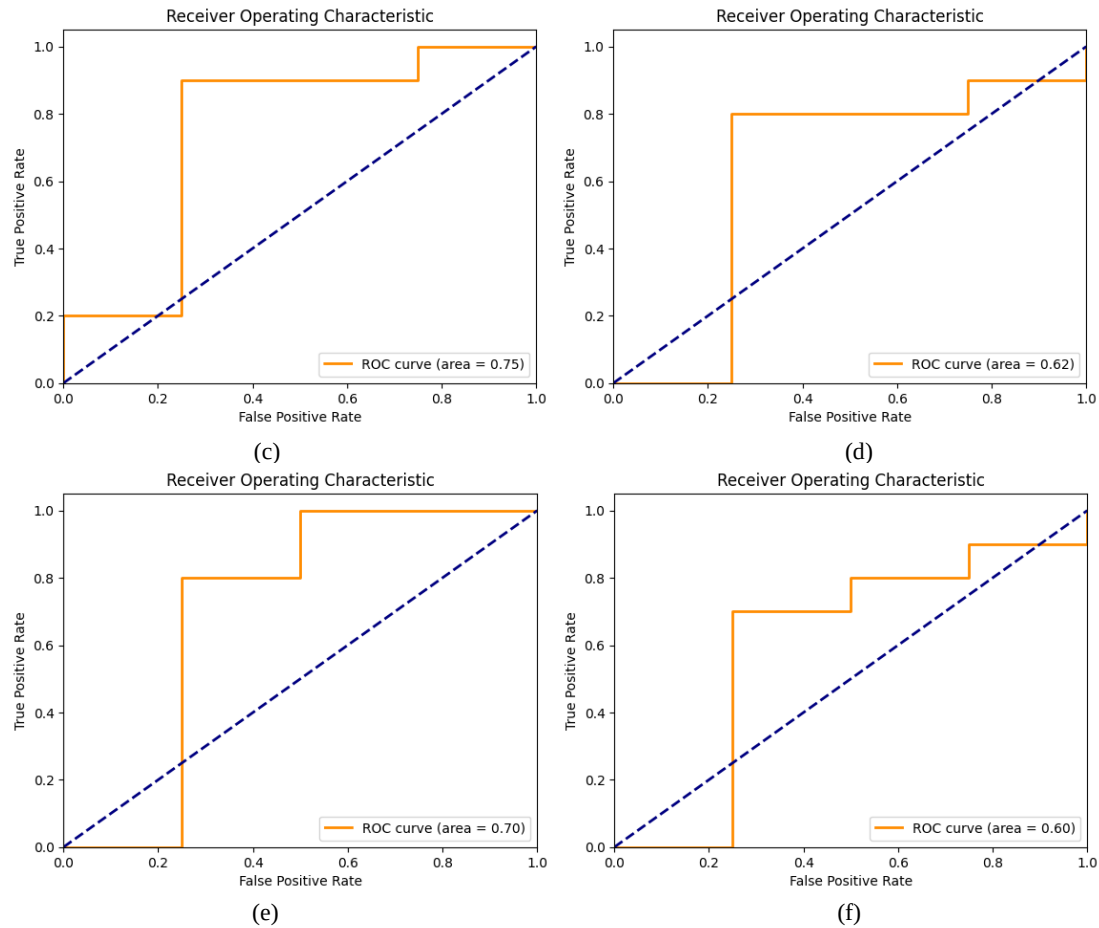


Figure 3: ROC curves for (c) Model 4 (d) Model 5 (e) Model 6 (f) Model 7

During the current year (Model 1), the model exhibits optimal performance in achieving exceptional accuracy (0.93), precision, recall, and F1-scores, indicating strong predicting capability at the distress threshold. The model's effectiveness progressively declines, with a significant fall commencing in Model 3 as the forecast horizon expands beyond the current year. The model has considerable challenges at $T-4$ and $T-5$, with accuracy falling below 0.50, suggesting that prediction accuracy diminishes as the temporal distance from the distress event increases. This study demonstrates that while the model may affectively anticipate financial difficulty as it approaches, its predictive efficacy diminishes when forecasting distress farther in advance, especially over a three-year horizon.

A detailed analysis of predictive accuracy reveals how the effectiveness of the logistic regression model varies over time. As shown in Table 6, the model's accuracy demonstrates significant fluctuations based on the proximity to the distress event. In the year of distress

(Model 1), the model achieves its highest accuracy at 93%, indicating its robust performance when financial instability is most evident. One year prior to the distress event (Model 2), the accuracy remains high at 71%, suggesting that early warning signs are still reliably captured. However, as we move further back in time to $T-2$, $T-3$, and beyond, the accuracy declines to 64%, 57%, and 50%, respectively. This trend indicates that the model's predictive power diminishes as the time frame extends further from the distress event, highlighting the challenges in using traditional financial ratios for long-term forecasts.

The model's performance is highly influenced on the proximity to the distress occurrence. The ROC curve analysis shows that the model performs exceptionally well in the current year (Model 1) with an AUC of 1.0, indicating perfect classification of distressed and non-distressed companies. This result is expected as companies nearing financial distress often exhibit clear signals such as deteriorating liquidity, profitability, and retained earnings, making predictions highly reliable. Nonetheless, as the prediction horizon extends further, the model's effectiveness decreases.

One year prior to distress (Model 3), the AUC remains high at 0.8, suggesting that early financial warning signals are still identifiable with good accuracy. Two years before distress (Model 4), the AUC drops to 0.75, reflecting a moderate reduction in the model's ability to predict distress. This decline persists in Model 5, where the AUC reaches 0.625, signifying that the model is only slightly better than random guessing. These findings suggest that financial indicators become less reliable predictors as the prediction window extends, likely due to the less pronounced financial instability at earlier stages.

Interestingly, the AUC increases slightly in Model 6 (0.7), suggesting the presence of latent financial trends that become identified prior to distress crisis. Despite this slight improvement, the model's overall predictive power remains limited, with accuracy significantly reducing to 0.6 in Model 7.

While the logistic regression model offers valuable insights into predicting financial distress, it is important to recognize its limitations in comparison to more advanced modelling techniques. Specifically, logistic regression may fall short in its ability to capture complex, non-linear relationships and interactions among variables, which are strengths of machine learning techniques such as decision trees, random forests, and neural networks.

To enhance the robustness of financial distress predictions, future research should include a comparative analysis of logistic regression with these advanced models. Such a comparison would not only highlight the strengths of advanced techniques in handling complex data patterns but also identify specific contexts where logistic regression retains advantages, particularly in terms of interpretability and ease of implementation.

By thoroughly examining the strengths and weaknesses of both approaches, future studies can provide a more detailed understanding of the relative performance of logistic regression against contemporary predictive modelling techniques in the realm of financial distress prediction. This comprehensive analysis will guide practitioners in selecting the most appropriate modelling approach based on their specific needs and contexts.

6. Conclusion

This study aimed to create a logistic regression model to predict financial distress among Malaysian companies using financial ratios. The findings indicate that the model is most effective in the short term, particularly within the year of distress and up to one year prior to the event, where predictive accuracy is highest. Key financial indicators such as working capital, retained earnings, and EBIT are pivotal in determining a company's likelihood of distress, reflecting the critical importance of liquidity, profitability, and financial stability.

However, as the prediction horizon extends beyond two years, the model's accuracy declines, signalling the limitations of using traditional financial ratios for long-term predictions. This suggests that while logistic regression is a valuable tool for near-term distress prediction, its effectiveness diminishes in early-stage forecasts, where distress signals are less pronounced.

The study's findings also highlight the necessity for continuous monitoring and timely intervention as companies approach financial distress. For practitioners, investors, and policymakers, focusing on key financial ratios closer to the distress event provides more reliable insights for decision-making. Future research should investigate the integration of additional variables and advanced modelling techniques to enhance predictive accuracy for long-term financial distress forecasting.

To improve the model's predictive accuracy, it is essential for future research to address calibration issues through regular revaluation of model specifications and the inclusion of relevant variables. Additionally, integrating non-financial indicators such as market sentiment and macroeconomic factors can offer a more comprehensive assessment of a company's health. Employing advanced calibration techniques, like Platt scaling or isotonic regression, will also enhance the alignment between predicted probabilities and actual outcomes, particularly for long-term predictions. By pursuing these strategies, future studies can strengthen the reliability of logistic regression models in forecasting financial distress. It is also recommended to explore more advanced models alongside logistic regression such as Random Forest, Support Vector Machine and Neural Networks which can offer more comprehensive understanding of which model is most effective.

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